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Analysis

Technology Diffusion and Climate Policy: A Network Approach and its Application to Wind Energy☆

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ABSTRACT

The role of technology transfer in the mitigation of climate change has been strongly emphasized in the recent policy debate. This paper offers a network-based perspective on the issue. First, we propose a methodology to infer from technology adoption data the network of diffusion and apply it to a detailed dataset on wind energy technologies installed globally since the 1980s. We then perform a statistical analysis of the network. It highlights a relatively inefficient organization, characterized in particular by the weakness of South-South links, which leads to relatively long lags in the diffusion process. Against this background, we characterize optimal transfer/seeding strategies for an agent that aims to introduce a new technology in a developing country in view of further diffusion. Our results suggest in particular that CDM projects have been too concentrated in large emerging economies and that developed countries should put a stronger weight on the positive externalities in terms of technology transfer of cooperating with less prominent developing countries.

1. Introduction

Technology transfers are put forward prominently, both in the Intended Nationally Determined Contributions (INDCs) and in the text of the COP21 Paris Agreement, as necessary conditions for the implementation of an effective mitigation policy at the global scale. Explicitly, the Paris Agreement emphasizes the need of "***technology** and capacity-building **support by developed country Parties**, in a predictable manner, to enable enhanced pre-2020 action by developing country Parties*.[1]" This requirement implicitly assumes that technology transfers can be heavily influenced or even controlled by the governments of developed countries. This might be true in some very specific industries such as defense and aerospace. Yet, for most of the technologies that are of concern for climate policy, notably renewable energy, the diffusion process is the outcome of interactions between private firms. Moreover, transfers take a wide variety of forms (e.g. material or immaterial) and employ a variety of vehicles (see Haug, 1992 for an extensive discussion). In this complex landscape, it is much less clear what policy can do and how it can operate.

The existing literature on the transfer of climate related technologies has mainly emphasized the role that domestic policy in developing countries can play by providing enabling conditions for adoption and development of technologies (see e.g., de Coninck and Sagar, 2015 and references therein). This is an important conclusion but it does not provide any insight on the measures developed countries should take in order to fulfill the commitment to support technology transfers that they have taken in the framework of the Paris Agreement.

In order to address this issue, a prerequisite is to understand the existing dynamics of technological diffusion. Therefore, this paper proposes a methodology to infer, from adoption data, the structure of the network of technology diffusion between countries. A first type of policy measures that can then be analyzed in this framework is the subsidization by developed countries of the installation of certain technologies in developing countries, in view of fostering their further diffusion. This is one of the direct objectives of the Global Environment Facility (see e.g., GEF, 2014) and an indirect objective of the Clean Development Mechanism (see e.g., UNFCCC, 2010). A broader issue is the extent to which policy-makers can, individually or collectively, modify the network of diffusion. This is however beyond the scope of this paper as it requires to infer the determinants of network formation rather than the network per se.

Accordingly, wind energy being one of the most important

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[1] Our emphasis; see also articles 66 to 71 of UNFCCC (2015).

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technologies for climate change mitigation (e.g., see IPCC, 2011), we apply our methodology in this context, using a comprehensive database on wind turbines installed globally from 1983 onwards. We hence provide an empirical contribution by identifying existing inefficiencies in the wind technology diffusion network and by characterizing how policy can best operate given the existing network structure.

Our main conceptual innovation is to adopt a network-based approach, whereas the existing literature has mainly focused on bilateral transfers in the Clean Development Mechanism (CDM) framework (see de Coninck and Sagar, 2015 and references below). This allows us to provide a systemic perspective that accounts for the impact of each country not only on its direct connections, but also on the global diffusion process. Indeed, a country might be quantitatively neither the most important source nor the most important adopter of a technology, but still play an important role as a hub in its diffusion. The fundamental role of such network effects has been identified in a wide range of contexts such as epidemics (see e.g., Pastor-Satorras and Vespignani, 2001), social dynamics (see e.g., Castellano et al., 2009), spatial econometrics (see e.g., LeSage and Pace, 2009; Elhorst, 2014), or the diffusion of innovations (see e.g., Rogers, 1983).

From the methodological point of view, an important difficulty is that technology diffusion networks are generally not directly observed. To address this issue, we build on the independent cascade model of Gomez-Rodriguez et al. (2010, 2011, 2014) and infer the structure of the network by maximizing the likelihood of the observed patterns of technology adoption using a parametric model of diffusion. This allows us to reconstruct the global wind diffusion network and its evolution over time. We then perform a statistical analysis of the network. It highlights a relatively inefficient organization, characterized in particular by the weakness of South-South links, which leads to relatively long lags in the diffusion process. Against this background, we characterize optimal transfer/seeding strategies for an agent, such as the GEF or a developed country engaging in development policy, that aims to introduce a new technology in a developing country in view of further diffusion. The more structural question of how policy can modify the structure of the network in order to increase the efficiency of the diffusion dynamics is not addressed here although we recognize its importance.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 outlines the methodology and Section 4 its application to the diffusion of wind energy, followed by quantitative analyses of the network. Section 5 then aims at appraising efficient strategies for technological diffusion in the context of climate policy. Section 6 concludes and raises ideas for further research.

2. Related Literature

The importance of technological diffusion processes for the achievement of climate policy objectives has been emphasized at least since the Kyoto Protocol (see e.g., Blackman, 1999). Within the scientific community, the Intergovernmental Panel on Climate Change (IPCC) has repeatedly put forward its central role for climate policy and sustainable development (see e.g., IPCC, 2014). In the policy debate, technology transfers are strongly emphasized in the INDCs prepared for the COP21 and their relevance is recognized in the Paris Agreement which puts forward in its preamble "*the urgent need to enhance the provision of finance, technology and capacity-building*" and devotes a full section to its decisions on "technology development and transfer," hence putting it on an equal footing with mitigation and adaptation.[2] Despite this emphasis, our understanding of how technology diffuses globally and of how policy can influence the process remains very partial. This is explained in part by a lack of detailed data on technology transfer, as well as by the fact that the process itself is complex, making policy in this area especially challenging (cf. Maskus, 2004; de Coninck and Sagar, 2015).

Three main market channels of technology transfer have been distinguished in the literature (cf. Glachant et al., 2013): (i) international trade in intermediate goods (e.g., export and import of equipment), (ii) foreign direct investments including joint ventures, and (iii) licensing.[3] Accordingly, there has been a focus on explaining bilateral flows of environmentally friendly technologies using measures such as international trade data, FDI, and patents (e.g., Popp, 2005; Popp et al., 2011; Glachant et al., 2013; Dechezleprêtre et al., 2013). In particular, Dechezlepretre and Glachant (2014) investigate the role of policy in fostering technology transfer in wind energy, where technology transfer is defined as a patent application filed by an inventor residing in a country that is different from the one in which protection is sought. In terms of encouraging transfer, public policy support is highlighted, but it should be pointed out that annual wind power generation in each country is used as a proxy measure for demand-pull policies.[4] Also to keep in mind is that certain types of knowledge that are tacit are not patentable, and that innovation activity is highly concentrated in a few countries (cf. ibid).

In the specific context of climate policy, the Clean Development Mechanism has been considered as an important, and well-documented source of technological transfers leading to a number of studies on the magnitude and the drivers of bilateral transfers of renewable energy technologies (in particular Dechezleprêtre et al., 2008, 2009; Popp, 2011; Schneider et al., 2008; Weitzel et al., 2015; Murphy et al., 2015). The focus there is on transfers of low-carbon technologies from developed to developing countries. It should be stressed, however, that technology transfer was only a secondary focus of CDM projects whose main objective rather was to reduce abatement costs. In particular, it should be noted that not all CDM projects entail an actual international technology transfer; in fact, it has been shown that transfers take place in less than half of CDM projects (Dechezleprêtre et al., 2008). Though they have contributed to implementing wind power projects (see e.g., Timilsina et al., 2013), there has also been much debate on the effectiveness to enhance transfers, with critiques including the profit-maximizing view of behavior underlying the institutions and that technology transfer is not solely a developed or developing country issue (cf. Zografos and Howarth, 2010; de Coninck and Sagar, 2015). Considering the dominant North-South focus, and as stressed in Brewer (2008) who proposes a shift to a 'global paradigm,' it is interesting to explore South-South transfers, and altogether not make such dichotomous distinctions.

Another important issue is that most CDM projects have been directed to the large emerging economies, mostly China, India, and Brazil (Dechezleprêtre et al., 2008; Rahman et al., 2016).[5] This leaves out a significant amount of smaller low and middle-income countries. In this respect, the data and approach we use is more inclusive in terms of geographical coverage with countries that are less in the spotlight in the technology transfer and climate policy domains, and also allows going beyond a bilateral North-South transfer perspective. Also, though data from the project design documents of the CDM is detailed, a significant limitation is that data of projects are usually registered during a very short period (around 2 years; ibid), thereby not allowing to analyze the *dynamic* aspects of diffusion, being the accumulation of technology across adopters and over time arising from adoption decisions (Comin

[2] As with technology, the role of finance in inducing the low-carbon transition is also receiving increased attention and for a recent paper on this latter issue see for example, Campiglio (2016).

[3] Non-market channels such as migration are much less explored.

[4] For the EU, Serrano-Gonzalez and Lacal-Arantegui (2016) also find barriers to wind energy (note they do not study technology transfer specifically), relate mostly to the political and economic framework, such as abrupt changes and retroactive measures including suspension of support schemes.

[5] Rahman et al. (2016) find that respectively, China, India and Brazil are the three largest host countries, with more than 72% of the projects in the CDM portfolio.

and Mestieri, 2014). More generally, an important challenge for research on technology diffusion is the lack of comprehensive datasets that directly document the diffusion of specific technologies across countries (Comin et al., 2013). In addition to geographic scope, the data used in our study is unique in this sense since it is possible to observe adoption patterns over a long period of time.

Finally, as highlighted in the introduction, previous literature has not explored the role of networks in the context of technological diffusion, instead concentrating on bilateral transfers treated independently for each country-pair. An exception is Rahman et al. (2016) who include a "neighbor" (knowledge transfer) effect with a variable measuring the number of similar types of projects in a given sub-region of the world, and find it is insignificant which they interpret as showing no evidence that projects are crowded out by other investments. However, this does not explicitly adopt a network approach addressing the role of interconnections (both direct and indirect) in the global diffusion of technologies. As underlined in a recent survey on the diffusion of green technology, networks can be fundamental in the spread of technologies (Allan et al., 2014).[6] In the theoretical literature, recent network models of innovation and technology diffusion (e.g., Centola et al., 2007; Montanari and Saberi, 2010; Acemoglu et al., 2011) provide insights on the influence of the network's topology on its dynamics. These models consider a wide range of diffusion processes ranging from epidemic-like contagion to strategic adoption and linear threshold models. Though conclusions on what facilitates diffusion are not clear-cut, the literature suggests that innovations spread further across networks with a higher degree of clustering. In principle, clusters can promote diffusion where a seed node exists inside them, but are more difficult to permeate when not targeted during the initial seeding phase.

In sum, we can distinguish two main approaches. The first are non-network studies such as the descriptive and econometric analyses on factors driving technology transfers, through for example, CDM projects. The other is on understanding how the topology of the network affects diffusion. It should be noted that in the social and economic network literature, the majority of studies are on how the network influences behavior (see e.g., Jackson, 2008), while the issue of network formation is still in its infancy in the empirical literature (see e.g., Chandrasekhar, 2016). A further challenge one faces when looking at technological diffusion at the global scale is that the network is unobserved. To overcome this issue, we build on the growing network inference literature (Saito et al., 2009; Gomez-Rodriguez et al., 2010; Gomez-Rodriguez et al., 2011; Daneshmand et al., 2014), which focuses on estimating network structures on the basis of observations of cascades (sequences) of technological adoptions. More precisely, the principle of the independent cascade model is to infer the maximum likelihood network under the assumption that each cascade is an independent instance of a continuous time diffusion process. The underlying models of diffusion in continuous time are related to the additive regression model used in survival theory analysis (see e.g., Aalen et al., 2008).

3. Network Inference Method

The cornerstone of our approach is to use the independent cascade model of Gomez-Rodriguez et al. (2010) to infer a network of technological diffusion from time-series of observations of the adoption/installation of subsequent generations of a technology within a country. The weights of the resulting network are interpreted as the rates at which an instance of the technology is likely to be transferred between countries. These weights summarize the effects of a number of latent variables that govern the bilateral diffusion between countries (e.g. the export strategy of firms, the flow of FDI or the existing trade and/or cooperation agreements between countries), and the systemic role that countries can play by serving as intermediaries in the global diffusion process.

More formally, we consider that we are given series of observations of the diffusion of subsequent vintages of a technology. Each vintage c is characterized by a cascade of adoptions $\boldsymbol{t}^c = (t_1{}^c, \ldots, t_N{}^c)$, which is an N-dimensional vector of observed activation times. More precisely, for each node i, t_i^c is an element in $[t_0{}^c, t_0{}^c + T] \cup \{\infty\}$, which is equal to the time at which country i adopted the technological vintage c if finite and is infinite if the country did not adopt the technology during a time interval of length T starting with the first adoption at time $t_0{}^c$. Note that the fact that a node is assigned ∞ as activation time does not mean stricto-sensu that the node did not get activated, but rather that his activation was discarded given the time-window considered as relevant. The data can then be represented by a set C of cascades, one cascade for every vintage, and denoted as $C \coloneqq \{\boldsymbol{t}^1, \ldots, \boldsymbol{t}^{|C|}\}$.

Our aim then is to infer from this data a diffusion network consisting in a pair (G, A) where $G = (V, E)$ is a graph (i.e. a set of nodes V and a set of edges E) representing the potential diffusion paths of the technology and $A = [\alpha_{j,\ i}]$ is a matrix of transmission rates, i.e. $\alpha_{j,\ i} > 0$ quantifies how likely it is that a technology spreads from node j to node i if $(j, i) \in E$ (and $\alpha_{j,\ i} = 0$ if $(j, i) \notin E$). The principle of the independent cascade model is to infer the maximum likelihood network under the assumption that each cascade is an independent instance of a diffusion process drawn from a parametric model in which the probability of diffusion from node j to node i is parameterized by the transmission rate $\alpha_{j,\ i}$ that is to be determined.

More precisely, the building block of our approach is the probability $f(t_i | t_j; \alpha_{j,i})$ that node i gets activated by node j at time t_i, given node j was activated at time t_j and assuming a transmission rate $\alpha_{j,\ i}$ between nodes j and i. One then says that node j is the parent of node i. The functional form of f conveys the structural assumptions about the diffusion process (see the discussion below). Now, given the conditional density $f(t_i | t_j; \alpha_{j,i})$, one can infer the likelihood of a set of cascades $\{\boldsymbol{t}^1, \ldots, \boldsymbol{t}^{|C|}\}$ given a network $A = [\alpha_{j,\ i}]$ as follows (see Gomez-Rodriguez et al., 2011 for a comprehensive discussion).

- First, given a cascade $\boldsymbol{t}^c = (t_1{}^c, \ldots, t_N{}^c)$, the likelihood of node i being activated by node j is given by:

$$f(t_i \mid t_1, \ldots t_N \setminus t_i; A) = \sum_{j: t_j \le t_i} f(t_i \mid t_j; \alpha_{j,i}) \times \prod_{j \ne k, t_k \le t_i} S(t_i \mid t_k; \alpha_{k,i}) \tag{1}$$

where $S(t_i | t_j; \alpha_{j,\ i})$ is the survival (anti-cumulative distribution) function of edge $j \to i$, that is the probability that j does not cause i to activate by time t_i. Indeed, assuming a node gets activated only once, one shall consider it is activated by node j only if it has not been activated before by another node in the cascade.

- One can then compute the likelihood of the activations in a cascade before time T as:

$$f(\boldsymbol{t}^c_{\le T}; A) = \prod_{t_i \le T} \sum_{j: t_j \le t_i} f(t_i \mid t_j; \alpha_{j,i}) \times \prod_{k: t_k < t_i, k \ne j} S(t_i \mid t_k; \alpha_{k,i}) \tag{2}$$

- Further, the likelihood of a cascade accounts for the fact that some nodes did not get activated (we consider that nodes not activated before time T never get activated). It is therefore given by

$$f(\boldsymbol{t}^c; A) = \prod_{t_i \le T} \prod_{t_m > T} S(T \mid t_i; \alpha_{i,m}) \prod_{t_i \le T} \sum_{j: t_j \le t_i} f(t_i \mid t_j; \alpha_{j,i}) \prod_{k: t_k < t_i, k \ne j} S(t_i \mid t_k; \alpha_{k,i}) \tag{3}$$

- Finally, the likelihood of a set of cascades $C = \{\boldsymbol{t}^1, \ldots, \boldsymbol{t}^{|C|}\}$, assuming each cascade is independent, is the product of the likelihoods of the individual cascades given by Eq. (3), that is:

$$f(\{\boldsymbol{t}^1, \ldots, \boldsymbol{t}^{|C|}\}; A) = \prod_{t^c \in C} f(\boldsymbol{t}^c; A) \tag{4}$$

The objective of the network inference problem then is to find $A =$

[6] For example, the benefits of using a given technology can depend on the extent to which others also use it (ibid).

$[\alpha_{j,\,i}]$ such that the likelihood of the observed set of cascades $C = \{\boldsymbol{t}^1, \ldots, \boldsymbol{t}^{|C|}\}$ is maximized. More precisely, we aim at solving the following maximum likelihood (ML) optimization problem:

$$\text{minimize } A - \sum_{c \in C} \log f(\boldsymbol{t}^c; A)$$
$$\text{subject to } \alpha_{j,i} \geq 0,\ i, j = 1, \ldots, N,\ i \neq j \tag{5}$$

In practice, we solve Eq. (5) using CVX, which is a general purpose package in MATLAB for specifying and solving convex programs (Grant and Boyd, 2015) and the algorithm NETRATE, which are publicly released open source implementations.

As emphasized above, structural assumptions about the diffusion process are embedded in the functional form chosen for the function f. Our baseline assumption will be to consider that once a country has adopted a technology, the probabilistic rate at which it diffuses it to one of its neighbor is constant over time (although it might depend on the neighbor under consideration). This amounts to considering the diffusion follows a Poisson process and therefore leads to an exponential model for the conditional density of diffusion over time (see e.g., Kingman, 1993). That is $f(t_i \mid t_j; \alpha_{j,\,i}) = \alpha_{j,\,i} e^{-\alpha_{j,\,i}(t_i - t_j)}$ (if $t_j < t_i$ and zero otherwise) where $\alpha_{j,\,i}$ is the diffusion rate. The Poisson assumption of a constant diffusion rate is a simple and natural benchmark in absence of specific information about the dynamic aspects of the diffusion strategies of micro-economic actors. In particular, a Poisson process emerges if diffusion opportunities are distributed uniformly across time, independently of whether diffusion is demand or supply driven.

In order to assess the robustness of our results to the assumption of a Poisson diffusion process, we consider as a potential alternative the power-law model for which $f(t_i \mid t_j; \alpha_{j,\,i}) = \alpha_{j,\,i}(t_i - t_j)^{-1-\alpha_{j,\,i}}$ (if $t_j < t_i$ and zero otherwise). As emphasized by Barabási (2005), this model can be seen as the outcome of a queuing process in which a decision-maker intervenes to set priorities. It leads to much fatter tails in the temporal distribution of events than the exponential distribution, consistently with empirical data about the timing of human-driven events. In our setting, it amounts to considering that most diffusion events are clustered near the activation time of the source node, while the remaining diffusions experience very large waiting times. A natural interpretation of this pattern is that countries generally adopt the latest vintage of a technology so that the bulk of adoptions should happen in a relatively short time-window after its inception before the technology becomes obsolete.

Independently of the underlying diffusion model, the network inferred by maximum likelihood provides two main types of information. First, the adjacency structure of the network indicates which routes technologies are likely to follow in their diffusion. Second, the weight of an edge gives an estimate of the speed at which diffusion is likely to occur between nodes. Note that this interpretation does not presuppose that diffusion is the outcome of a (rational) decision of countries, consistently with the epidemiological roots of the model. Similar to the reproduction and the diffusion of viruses, which are the outcome of micro-level phenomena beyond the control of the central nervous system, the diffusion of technologies is the outcome of the decisions of firms and households, which are for the most part beyond the control of the state. This does not imply that the state cannot influence the diffusion process through policy. However, in the following, we shall consider the national policy setting is fixed and rather consider policy interventions at the international level such as the exogenous inception of a technology in a country, for example through CDM like projects.

4. The Wind Energy Network

4.1. Context and Data

Wind energy is currently the most important source of renewable energy and has been growing exponentially in the last decades (see Fig. 1 as well as GWEC, 2015 and IEA, 2015). Therefore, it is expected

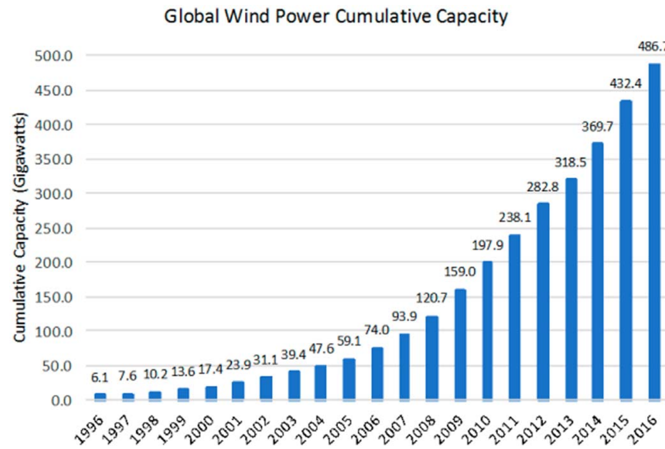

Fig. 1. Wind power capacity.
(Source: Global Wind Energy Council statistics)

to play a key role in mitigation policy globally (IPCC, 2011; Luderer et al., 2014). In this perspective, it is required that new generations of wind turbines diffuse rapidly at the global scale. A key empirical macro-level observation in this respect is that the geographical pattern of deployment is changing. Whereas OECD countries led early wind development, from 2010 non-OECD countries installed more wind turbines, and using scenario-based analysis it is predicted that after 2030 this will rise to more than 50% of global installed capacity (see OECD/IEA, 2013). This further emphasizes the need of efficient technological diffusion to ensure that the newly installed turbines are as close as possible to the technological frontier. Indeed, technological improvements of wind turbines since the 1980s has largely contributed to growth in wind power capacity. The general trend has been an overall growth in size, with an increase in the height of the tower, the length of the rotor blades and greater power capacity (see the Wind Energy Technology Roadmap report in OECD/IEA, 2013 for details).[7]

Now, very little observation data is available on the diffusion process of wind technology at the global scale. Understanding the structural properties of the network of diffusion of wind technology is nevertheless a prerequisite to determine how policy can contribute to faster technology transfers. In this perspective, the methodology we have introduced in the preceding section allows to infer the structure of the diffusion network from installation/adoption data, which is much easier to collect than diffusion data. As a matter of fact, the "Wind Power" database provides detailed technological and industrial information, as well as almost comprehensive coverage on the wind turbines installed worldwide from 1983 onwards.[8] Hence, it can be used to construct the cascades of successive technology vintages and therefrom infer the network of diffusion of wind energy using the maximum likelihood approach described in the preceding section. Table A5.1 in the Appendix provides details on the country, wind farm, and power capacity coverage for the 94 countries in the database. These include wind farms that have been installed and are in operation, as well as under construction, approved or planned within each country. As can be seen in the sample of the data provided in Table A5.2 in the Appendix, for wind farms with the status operating, there is information on the commissioning date. These are time series observations spanning the period from 1983 to 2016. The database also contains entries corresponding to wind farms under construction, approved and planned. To account for this data, conveying essential information on recent diffusion patterns, we assign the corresponding wind farms expected

[7] Klaassen et al. (2005) also provide more details on the impact of public R&D expenditures in promoting progress of wind turbine technology in their case study on Denmark, Germany, and the United Kingdom.

[8] Data available from http://www.thewindpower.net/.

commissioning dates of 2017, 2018, and 2019 respectively.

The uniqueness of the dataset is that in addition to the space and time information coverage of the wind farms, there is also precise data on power capacity and manufacturers of the wind turbines of the wind farms. This allows us to identify 240 vintages of technologies, which are mainly characterized by the size of the turbine and the manufacturer (e.g. as shown in Table A5.2, the Samsung 2500, the Vestas 2600 and so forth). One can then define one cascade per technology vintage as follows.

We consider countries as our nodes and set the activation time of a given technology vintage for a country as the commissioning date of the first wind farm in the country using the vintage. By convention, the activation time of a country not using the vintage is set to infinity. After excluding some countries of the dataset because of unavailable data,[9] we hence construct the cascades spanning 94 countries over a period of 37 years. We then proceed with the maximum likelihood estimation of the network following the procedure described in Section 3. We report in the main text results for the benchmark exponential model. Alternative results based on the power-law diffusion model are similar, both qualitatively and quantitatively, and reported in the Appendix.

4.2. Statistical Analysis of the Network

As illustrated in Fig. S1 (in the Appendix), the inferred network first provides a map of existing diffusion routes and hence a much broader view than obtained from the sole consideration of bilateral transfers.[10] For example, in our setting, it can be the case that countries x and y are not linked by a direct transfer, but that there exists a very short path from x to y through z, hence diffusion shall nevertheless occur relatively rapidly from x to y. On the contrary, the path from x to w could be relatively long (going through a, b, c, d, e, and so forth), which suggests a relatively long lag in the diffusion from x to w. Fig. S1 also puts forward the existence of a well-connected core mainly formed by the most advanced European countries surrounded by a periphery organized in geographical clusters, with large economies such as the United States prominent as well. This is consistent with the leading role played by firms and these countries in wind energy development over the past decades. Other countries such as China are coming more to the forefront, and these relatively more recent developments could result in a greater role in the network in the upcoming years. This also relates to the changing panorama of wind development made in the recent OECD/IEA (2013) report discussed above.

From a quantitative perspective, structural properties of the diffusion process can be characterized via a statistical analysis of the network. In this respect, key features of the network are reported in Table 1.

First, the basic measure of importance of a node is the degree, which measures its number of connections. In a directed network, one distinguishes the in-degree (number of incoming links) and the out-degree (number of outgoing links). In the context of technological diffusion, they respectively measure the direct potential to adopt or spread a technology. The inferred network has 596 edges, i.e. 596 links among the 94 countries. In other words, the average degree is approximately 12.6 and the network density, i.e. the ratio between actual and total potential number of links is 0.07. These values are in line with those generally observed in socio-economic networks (see e.g., Albert and Barabási, 2002; Chandrasekhar, 2016). The power-law model infers more links than the exponential one (see Appendix), consistently with the fact that the diffusion process decays more rapidly in the former case. Indeed, more links are then necessary to explain the same "volume" of observed diffusion.

Table 1
General properties of the network.

Overall network characteristics	Exponential model	Power-law model
Number of nodes	94	94
Number of links	596	752
Network density	0.068	0.086
Mean degree	12.681	16
Mean path length	2.905	2.548
Network diameter	8	6
Mean clustering coefficient	0.146	0.299

Then, the basic measure of distance between two nodes is the shortest path, also known as the geodesic distance, which corresponds to the length of the path that connects them with the smaller number of edges. The average path length of the network is then computed by summing up all the shortest paths and dividing by the total number of pairs. In the context of technological diffusion, the average path length can be seen as a measure of the average technological distance between two countries and in our setting, it has a value 3. This is relatively large with respect to the random graph benchmark usually satisfied by socio-economic networks (Albert and Barabási, 2002) and for which the average path length corresponds to the log ratio between number of nodes and average degree (1.8 in our setting). This conclusion holds independently of the choice of the exponential or power-law model of diffusion.

Furthermore, the diameter of the network (the shortest path between the two most distant nodes) has a value of 8 in our setting (6 for the power-law model), which is again relatively large with respect to the random graph benchmark (it ought to be close to the average path length following equation (16) in Albert and Barabási, 2002). These relatively large diameters and average path lengths hint at the existence of relatively long lags in the diffusion processes. Reinforcing evidence also emerges in Fig. S1, where one can observe that certain countries (e.g., Bolivia and Peru) are very loosely and indirectly connected to the core of the network and, more generally, that there are weak interconnections between the different regional clusters. Hence the current wind technology diffusion network displays a certain level of inefficiency. In particular, there might be significant delays between technology adoption in advanced and developing countries. It also reinforces the point in Section 2 on encouraging overall cross-border exchange, such as South-South transfers.

To further investigate this issue, we have performed a regional-level analysis, which reinforces these observations. It is apparent from both Table 2 and the diagonal elements of the matrix in Table 3 that Europe has by far the greatest amount of total and intraregional connections, indicating that activity is highly concentrated. Europe also has the largest off-diagonal elements, reflecting it is the most integrated area in the diffusion network. Though this region also has the most country coverage, still, its presence is clearly prominent. The most interregional flows are between Europe and Asia, followed by Europe and America.

It is also informative to evaluate these figures following the United Nations Framework Convention on Climate Change (UNFCCC), where Parties are organized into five regions: African Group, Asia-Pacific Group, Eastern European Group, Latin American and Caribbean Group (GRULAC), and the Western European and Others Group (WEOG). These groups are based on the tradition of the UN, and the others in WEOG include Australia, Canada, Israel, New Zealand, Turkey, and the United States.

This subdivision reveals complementary insights. It is even more apparent that especially the WEOG countries are the most important hubs, both in terms of links among themselves, as well as links with the other regional groups (see Tables 4 and 5). In fact, compared to other regions, the diagonal elements far exceed the off-diagonal elements. In contrast, for example, the Asia-Pacific region has much more

[9] In particular, these are Albania, Chad, Curacao, Mozambique, Namibia, Panama, Tanzania, and Vanuatu. Also, there is no data altogether for Guyana and Indonesia.

[10] The node size in the figures correspond to the betweenness centrality measure whose definition is recalled below.

Table 2
Regional-level statistics.

Id	Region	No. of countries	In-degree	Out-degree	Source region (%)	Target region (%)	Total degree
1	Africa	14	35	33	5.53	5.87	68
2	America	22	113	118	19.80	19.13	231
3	Asia	20	106	104	17.45	17.79	210
4	Europe	35	322	319	53.52	54.03	641
5	Oceania	3	20	22	3.69	3.36	42

Table 3
Matrix of intra- and interregional connections.

	Africa	America	Asia	Europe	Oceania
Africa	3	5	10	14	1
America	9	36	22	48	3
Asia	3	21	17	60	3
Europe	18	47	52	190	12
Oceania	2	4	5	10	1

Table 4
UN regional grouping statistics.

Id	Region	No. of countries	In-degree	Out-degree	Source region (%)	Target region (%)	Total degree
1	Africa	14	35	33	5.53	5.87	68
2	Asia-Pacific	18	89	97	16.28	14.93	186
3	Eastern Europe	17	93	111	18.62	15.60	204
4	GRULAC	20	77	93	15.60	12.92	170
5	WEOG	25	302	262	44.00	50.67	564

connections with WEOG countries than countries within the own region. Interestingly, based on the distribution of exported climate-mitigation inventions using patent data, Dechezleprêtre et al. (2011) also find that technology is mainly exchanged between industrialized countries, while transfers are almost nonexistent between developing countries. To illustrate, Fig. 2 shows the interconnections among the regions with the size of nodes and darker color corresponding to total degree (both intra- and inter-regional). The regional-level analysis based on the power-law model results are similar (see Tables 4.1 and 5.1 in the Appendix). For example, in both cases the within-region links in WEOG amount to around 28%, while they are only around 10% for the Eastern European Group.

To gain more quantitative insights on the issue, we provide a systemic characterization of the network via its degree distribution, which is constructed by computing for each potential value of the degree, the number (or the share) of nodes assuming that particular value. The degree distribution hence summarizes the structure of the network. The out-degree and in-degree cumulative distributions of the wind network are shown in Fig. 3 in log-log scale. The distribution clearly has fatter tails than normal, consistently with the presence of highly connected nodes in the core.

The middle range of the distribution even seems to follow a power law. The Kolmogorov-Smirnov statistics fail to reject the hypothesis that the data could have been drawn from the fitted power-law distribution (the KS-statistics are 0.163 (p-value = 0.97) for the in-degree distribution and 0.124 (p-value = 0.98) for the out-degree distribution).[11] However, the right tail of the distribution clearly drops faster than that of a power law.

Table 5
Matrix of intra- and interregional connections for UN regional grouping.

	Africa	Asia-Pacific	Eastern Europe	GRULAC	WEOG
Africa	3	6	4	6	14
Asia-Pacific	3	17	21	14	42
Eastern Europe	5	15	21	10	60
GRULAC	9	15	13	23	33
WEOG	15	36	34	24	153

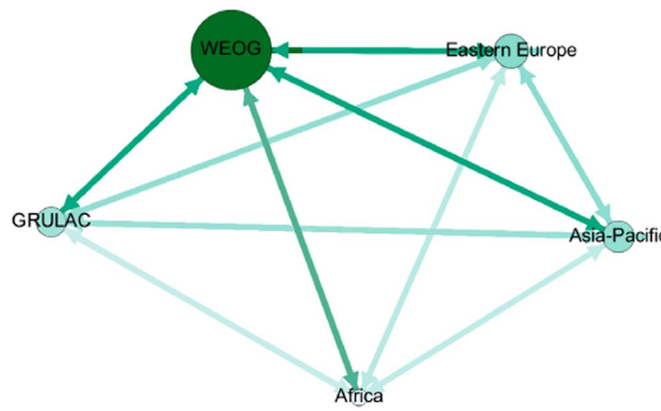

Fig. 2. Network connections at regional level.

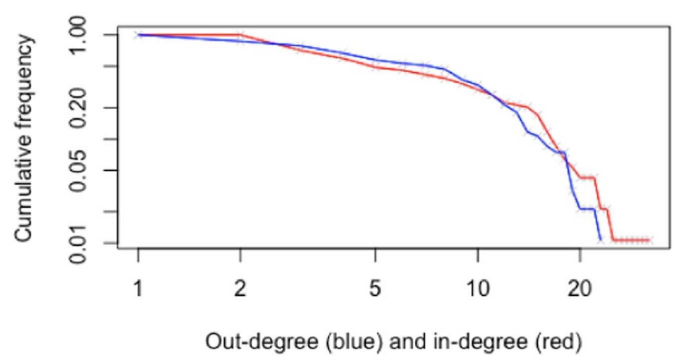

Fig. 3. Cumulative distribution of countries' out-degree and in-degree.

Also, the power of the K-S test is relatively low, especially to test heavy-tailed distributions, and thus the Anderson-Darling test which gives more weight to the tails is also considered (cf. Razali and Yap, 2011); these results indeed reject the null in most cases.[12] This indicates the lack of very large nodes that would play the role of central hubs in the diffusion process and hence increase its efficiency. A useful theoretical benchmark in this respect is the distance-based utility model of Jackson (2008), which shows that in a setting where the social objective amounts to minimizing distances in a network, the star would be the efficient network. A graphical comparison then suggests that the existing wind network has a much less hierarchical structure with a relatively large number of nodes with medium connectivity, but no clear center.

In order to further understand the origins of the current structure, our methodology can be used to simulate the network formation process by running the network inference algorithm for sub-periods of increasing lengths. The results of this analysis are presented in Fig. S2 in the Appendix. They can be compared with benchmark network formation processes such as preferential attachment, according to which entering nodes should connect

[11] The KS-statistics from the power-law model results are very similar, namely 0.137 (p-value = 0.98) for the in-degree distribution and 0.186 (p-value = 0.91) for the out-degree distribution.

[12] We thank an anonymous referee for bringing up this point. For the exponential model, the AD-statistics are 0.967 (p-value = 0.012) and 2.34 (p-value $<$ 0.001) for the in- and out-degree distributions; for the power-law model, they are 4.06 (p-value $<$ 0.001) and 0.334 (p-value = 0.484), respectively.

Table 6a
Rankings based on simulations.

Africa		Asia		Latin America	
(i)	(ii)	(i)	(ii)	(i)	(ii)
Cape Verde	Algeria	Thailand	Thailand	Colombia	Puerto Rico
Mauritius	Egypt	Taiwan	Vietnam	Guatemala	Guatemala
Seychelles	Mauritius	Vietnam	Taiwan	Ecuador	Nicaragua
Tunisia	Tunisia	Turkey	Pakistan	Puerto Rico	Bolivia
Morocco	Kenya	Russia	Philippines	Nicaragua	Ecuador
Egypt	Seychelles	Pakistan	Russia	Honduras	Honduras
Mauritania	Mauritania	Bangladesh	Turkey	Mexico	Brazil
Kenya	Morocco	South Korea	South Korea	Costa Rica	Uruguay
Algeria	Cape Verde	Philippines	India	Brazil	Chile
South Africa	South Africa	India	Bangladesh	Bolivia	Mexico
Eritrea	Eritrea	China	China	Uruguay	Cuba
Ethiopia	Ethiopia	Japan	Japan	Cuba	Argentina
Gambia	Gambia	Sri Lanka	Sri Lanka	Argentina	Colombia
Nigeria	Nigeria	UAE	Mongolia	Peru	Costa Rica
		Mongolia	UAE	Chile	Peru
		Jordan	Jordan	DR	DR
		Azerbaijan	Azerbaijan	Venezuela	Venezuela
		Iran	Iran		
		Israel	Israel		
		Kazakhstan	Kazakhstan		

Remark: Note that our results could also be partly due to the fact that high-degree nodes tend to have lower weights associated to their links by the diffusion model. Indeed, given that each bilateral diffusion is assumed to be independent, high-degree nodes are somehow expected to diffuse each technology they adopt to all their neighbors, which they obviously do not. As a matter of fact, some of the best performing countries according to Table 6a have much lower degree than the major economies of their regions. In order to test the robustness of our approach to this issue, we have repeated our analysis on an unweighted version of the diffusion network. The corresponding results are reported in Table S1 in the Appendix. "Small" countries identified as efficient hubs in the preceding simulation generally remain so but the performance of large regional hubs also increase.

to existing nodes with a probability proportional to the latters' degree.

A first key observation is that the growth of the network has been remarkable, expanding considerably both in terms of size and of connectivity. Compared to Fig. S1, the landscape for the earliest sub-period is much less dense and made up of a few major economies such as Denmark, a pioneer in developing commercial wind power. In the following sub-period, 1983–2000, it can be seen that the major players are Austria, Denmark, Germany, Greece, Ireland, the Netherlands, Spain, and the United Kingdom in Europe, which branch among themselves as well as with mainly China, Japan, and the United States. It can still be seen that there are much less countries in the network, such as South Africa which reflects that large-scale wind farms did not pick up there until the later 2000s.

Comparing Fig. S1 with the sub-period 1983–2005, three main changes come into view: the concentration in Europe is much greater (e.g., Belgium, Denmark, Germany, and Sweden have very high betweenness), China, India, Japan, and New Zealand are also more prominent in their respective regions, and other areas in the world are much less represented (e.g., Latin America). For 1983–2010, the network is still less dense, and importantly there is still less of a presence of some regions such as Latin America. The United States is quite more prominent in the network, as well as India and South Korea. Though sub-period 1983–2015 is as expected similar to Fig. S1, in general, there have been significant topological changes reflecting the vastly dynamic nature of the wind energy diffusion network. It also emerges, in particular, that a number of links are formed between countries entering the network contemporaneously, and this divergence from preferential attachment might help explain the lack of a single or only a few prominently central nodes in the network. This explanation is further backed by the fact that the assortativity coefficient of the network is positive (though small, equal to 0.112). Indeed, positive assortativity indicates that nodes tend to link to peers with the same or similar degree.

4.3. Centrality Analysis

To further investigate the role and position of hubs in the network, several centrality measures developed in the literature can be used in our framework (see Jackson, 2008 for an overview):

- The degree centrality of node i, which is simply given by its degree.
- The closeness of node i, $1/\Sigma_j d(j,i)$, is based on the average distance of i and hence measures how fast a technology seeded in one country would, on average, reach another country in the network.
- The betweenness centrality of node i measures the share of shortest paths in the network on which node i lies (see Appendix for a formal definition). Hence, in our context, it measures to which extent a country can serve as a hub in the diffusion process.
- The eigenvector centrality is a recursive measure that assigns a high value to nodes which are connected to other important nodes (see Appendix for a formal definition). In context, it can be seen as a measure of the total diffusion range (direct and indirect) of a technology, as a function of the seed country.

Table S2 and Fig. S3 in the Appendix provide an overview of the distribution of centrality in the network. It is clear that among the most predominant countries are France, Germany, Ireland, Italy, Spain, Sweden, Turkey, the United Kingdom, and the United States. In fact, many overlap across the different centrality measures. Canada, Denmark, Finland, and Hungary also appear among the top for some of the indicators. In addition, it can be observed that some emerging economies including the major BRICS, with the exception of Russia, have a strong presence, especially Brazil and China.[13] Although out-degree can be seen as reflecting a spreader of technology, with a higher number implying greater coverage, in-degree can also be a key indicator of the receptiveness to the technology. Since the diffusion process involves the accumulation of technology over space and time arising from adoption decisions, both the ability to spread and absorb new technologies are interrelated and important. In aggregate, main hubs are France, Germany, the United Kingdom, and the United States. With respect to closeness centrality, which provides an indication of which countries can reach all other reachable nodes quickly, Turkey, Hungary, Spain, Germany, Italy, the United States and United Kingdom

[13] As in the previous section, the power-law model centrality analysis results are also qualitatively similar.

Table 6b
CDM wind projects.
Source: CDM Pipeline Data produced by Jørgen Fenhann, UNEP and DTU Partnership.

Africa		Asia		Latin America	
(i)	(ii)	(i)	(ii)	(i)	(ii)
South Africa	15	China	1521	Brazil	69
Morocco	7	India	822	Mexico	30
Kenya	5	South Korea	13	Chile	19
Egypt	4	Pakistan	8	Uruguay	13
Tunisia	2	Vietnam	5	Argentina	11
Cape Verde	1	Philippines	5	Costa Rica	6
Mauritius	1	Sri Lanka	5	DR	6
Seychelles	0	Thailand	3	Nicaragua	4
Mauritania	0	Azerbaijan	2	Peru	4
Algeria	0	Israel	2	Ecuador	3
Eritrea	0	UAE	1	Honduras	2
Ethiopia	0	Mongolia	1	Colombia	1
Gambia	0	Iran	1	Guatemala	1
Nigeria	0	Taiwan	0	Puerto Rico	0
		Turkey	0	Bolivia	0
		Russia	0	Cuba	0
		Bangladesh	0	Venezuela	0
		Japan	0		
		Jordan	0		
		Kazakhstan	0		

are among those taking top positions.

Betweenness centrality is particularly insightful. As previously discussed, it determines the relative importance of a country by measuring the amount of flows through that country to other countries in the network, thus acting as a bridge. This relates back to the importance of the network approach discussed previously, and in particular, the value of technology intermediaries encouraging interaction within a system (IPCC, 2000). The visualization of the network based on the betweenness indicator (Fig. S1) highlights the importance of both regional and global hubs in the wind energy diffusion network. For example, Brazil for Latin America, Canada and the United States in North America, France in Europe which is evidently very central in the network, Turkey for Eurasia, Australia for Oceania, and South Korea, as well as China and Japan for Asia. Eigenvector centrality builds upon degree centrality, also taking into account the quality of the connections, i.e. how connected a country is to hubs in the wind energy diffusion network. France, the United States, the United Kingdom, Germany, Sweden, Finland, and China are among the most important actors in the network according to this measure (see Fig. S3). It should be noted that some of these are also hubs themselves, while some countries such as Croatia and Denmark do not overlap over these measures.

Hence, the comparison between centrality measures reinforces the conclusion of the preceding section: there is only partial overlap between the different centrality measures and the distribution of centrality among top nodes is relatively uniform. In this sense, the network is multipolar and no single node appears as an evident center. Therefore, it is not straightforward to put forward a node, nor a region, as the optimal target for the inception and the diffusion of new vintages of wind technology.

5. Efficient Diffusion Strategies

In view of the inefficiencies identified above, it is clear that there is a large room for policy-driven improvements in wind technology transfers. A priori, one can distinguish three types of policy measures that could foster the diffusion process. First, international agreements on technology, trade and the environment (e.g., climate clubs, see Nordhaus, 2015; Grubb et al., 2015) that could reshape the structure of the network. Their analysis requires an understanding of the economic determinants of network formation and hence is beyond the scope of this paper, which takes the diffusion network as given and focuses specifically on policy measures that developed countries can implement to foster diffusion towards developing countries. A second type of measures concern domestic policy in developing countries that shall provide enabling conditions for adoption and development of technologies. These have already been approached in the literature (see e.g., Lewis, 2007; Wang et al., 2012; de Coninck and Sagar, 2015; Dai and Xue, 2015) and seem mainly of concern for the BRIC group of countries. A third domain, that is of concern for policy-makers in developed countries is the subsidized diffusion of technologies in developing countries. This is the focus of large parts of cooperation and development policy, of the United Nations' global environment facility (GEF) and, indirectly, of the Clean Development Mechanism. This third domain is our central concern in this paper. Indeed, our network-based approach allows to frame the problem of technology transfer in this context as a problem of targeting on network (see Kempe et al., 2003) in which the policy-maker must choose a country or a group of countries in which to introduce/seed the new vintage of a technology in order to foster its further diffusion. In this perspective, network effects are fundamental. Therefore, we build on the network inferred in the preceding section to address empirically this issue.

We first approach the problem from the point of view of a social planner who aims at choosing a developing country in which to introduce a technology in order to maximize its spread in the network, in line with the objectives put forward by the UNFCCC (2015) of using technology transfers in order to foster climate change mitigation and economic development. The initial inception points can be seen as the initiator of the technology, but also as a partner country in which the technology is proactively diffused in the context of bilateral or multilateral technological cooperation or development aid. We then run a series of simulations in which we compare the performance of different inception strategies. More precisely, we aim to determine the developing country within a region that is the optimal target for technology inception with respect to two criteria: (i) the maximum time it takes for the country to spread to all other countries in their respective regions, and (ii) its ability to achieve the most technological deployment (i.e. the most coverage) in the region within two decades (which seems an approximately correct time-scale in the context of climate mitigation).

We solve these two optimization problems numerically. We first randomly draw (e.g., 1000 times) the activation times from the probability density function (pdf) of the exponential distribution using the transmission rates inferred in the preceding section. Then, using these

Table 7
Top 50 pairs based on shortest paths.

Id	Country *a*	Id	Country *b*	Efficiency gain *a*	Efficiency gain *b*
32	France	2	Argentina	1.25	1.5
32	France	3	Australia	1.25	1.5
32	France	9	Bolivia	1.25	1.75
32	France	10	Brazil	1.25	1.5
30	Fiji	11	Bulgaria	1.5	1.5
32	France	11	Bulgaria	1.25	1.5
56	Mauritius	11	Bulgaria	1.5	1.5
32	France	14	Chile	1.25	1.5
32	France	15	China	1.25	1.25
32	France	20	Cyprus	1.25	1.5
32	France	21	Czech Republic	1.25	1.25
32	France	24	Ecuador	1.25	1.5
80	Spain	30	Fiji	1.25	1.5
90	United-Kingdom	30	Fiji	1.25	1.5
92	USA	30	Fiji	1.25	1.5
38	Honduras	32	France	1.5	1.25
52	Lithuania	32	France	1.25	1.25
55	Mauritania	32	France	1.5	1.25
57	Mexico	32	France	1.25	1.25
58	Mongolia	32	France	1.5	1.25
62	Nicaragua	32	France	1.5	1.25
65	Pakistan	32	France	1.5	1.25
68	Poland	32	France	1.5	1.25
70	Puerto Rico	32	France	1.5	1.25
74	Serbia	32	France	1.5	1.25
80	Spain	32	France	1.25	1.25
84	Taiwan	32	France	1.5	1.25
85	Thailand	32	France	1.25	1.25
87	Turkey	32	France	1.25	1.25
90	United-Kingdom	32	France	1.25	1.25
91	Uruguay	32	France	1.5	1.25
92	USA	32	France	1.25	1.25
80	Spain	36	Grenada	1.25	1.25
90	United-Kingdom	36	Grenada	1.25	1.25
92	USA	36	Grenada	1.25	1.25
80	Spain	56	Mauritius	1.25	1.5
90	United-Kingdom	56	Mauritius	1.25	1.5
92	USA	56	Mauritius	1.25	1.5
80	Spain	63	Nigeria	1.25	1
90	United-Kingdom	63	Nigeria	1.25	1
92	USA	63	Nigeria	1.25	1
80	Spain	73	Saint Kitts and Nevis	1.25	1.25
90	United-Kingdom	73	Saint Kitts and Nevis	1.25	1.25
92	USA	73	Saint Kitts and Nevis	1.25	1.25
4	Austria	1	Algeria	1.25	1.75
8	Belgium	1	Algeria	1.25	1.75
12	Canada	1	Algeria	1.25	1.75
15	China	1	Algeria	1.25	1.75
17	Costa Rica	1	Algeria	1.25	1.75
18	Croatia	1	Algeria	1.25	1.75

activation times, we calculate the minimum costs (i.e. the minimum time it takes for country *i* to reach other countries *j*) and shortest paths using Dijkstra's algorithm.[14] The results are reported in Table 6a (as well as Table S1 and 8.1 in the Appendix). Results are similar for both diffusion models as the length of shortest paths differ, on average, less than 20% between the two models.

The most striking result is that the most important regional actors according to conventional centrality measures do not appear to be the most efficient hubs in terms of spreading potential of a new technology (in this case of wind power) to the rest of the countries in the region. For Africa, South Africa appears much below large northern African countries or Cabo Verde (which targets a 100% renewable energy supply by 2020). For the Asian regional group, Thailand, Vietnam, Taiwan, and Turkey are among the top-ranked. Though there is some overlap with the rankings based on the centrality measures, the simulation results imply that Southeast Asia and Taiwan have a more promising potential as spreaders of new technologies in the region than implied by the centrality measures whereas India and China fall short to a certain extent of their role as regional leaders. In view of the results of the preceding section (in particular Tables 3 and 5), this result can be explained by the fact that most of the interconnections of the BRIC countries, notably China and India, are with developed countries. Indeed, these countries were initially importers of technologies from developed countries and when they latter shifted to exporter status, developed countries became their main export market. In other words, their poor performance as regional hub for diffusion can be explained by the lack of South-South relationships, which in turn can be related to the lack of institutional schemes, akin to CDM or cooperation policy, to accompany these types of transfers.

In order to highlight the policy implications of these results, it is useful to contrast them with data about the volume of CDM wind projects by recipient country, which is provided in Table 6b. One observes a major contrast between the very large number of CDM projects in large emerging economies such as India and China and their role in the regional diffusion of technology. This observation is consistent with previous results in the literature (de Coninck and Sagar, 2015 and references therein) that show, through a detailed analysis of the CDM pipeline, that technology transfer is much less prevalent in CDM projects in the large emerging economies (mainly China, India and Brazil) compared to other countries, e.g., Indonesia and Thailand (de Coninck and Sagar, 2015).

From a policy perspective, this implies that positive external effects related to the role of the recipient country in the further diffusion of wind technology were hardly taken into account in CDM projects. In order to analyze how bilateral projects such as CDMs could be better used in view of fostering technological transfers, we perform a second series of simulations in which we consider that a new technology is initially seeded in a pair of two countries. One of the countries can be considered as the developer of the technology and the other as the target of a diffusion policy. The simultaneous inception of the technology in both countries can be interpreted as the creation of a new link in the network, i.e. a new trading route for the technology provider or the outcome of strengthened cooperation between the two countries. An alternative interpretation of these experiments is the inception by a third party of a new technology in multiple host countries simultaneously in order to obtain a wider coverage and to foster faster diffusion.

There are 4371 possible country pairs in our network. Using a simulation methodology similar to the one introduced for single countries, we rank the pairs in terms of the time required to diffuse the technology in the whole network and also determine an efficiency gain (for both countries in the pair) by computing the ratio between total diffusion times in the two seed case and the single seed case. Results are reported in Table 7.

A priori, the ranking of pairs has two main drivers. First, the centrality of the individual nodes in the pair matter as it determines the initial level of diffusion from which the new link can build. Second, the complementarity, in terms of distance to third countries, between the two nodes matter as it will determine the gain provided by the new link.

[14] This has been implemented using Joseph Kirk's code available on the file exchange of MathWorks. The outputs are an $N \times N$ matrix of minimum cost values for the shortest paths, and an $N \times N$ cell array containing the shortest path arrays where each element shows for each country, which countries are required to reach all other countries. To be noted is that the pdf of the exponential distribution in MATLAB is defined using an alternative parameterization, namely, $1/\alpha_{j,\,i} \times e^{-t_{j,\,i}/\alpha_{j,\,i}}$ if $t_{j,\,i} > 0$ and zero otherwise; hence we take the reciprocal of the transmission rates.

As a matter of fact, it turns out that the more efficient pairs are formed by a very central node (such as France, Spain, U.K, U.S.A, which have a high betweenness in the initial network) together with a node to which it was remotely connected in the initial network. Indeed, the high centrality agent provides a high initial diffusion potential while the newly created link to a distant node provides complementary connections to remote parts of the network. As a side effect, this provides an opportunity for the relatively remote countries to become more integrated in the network. These features can be related to the theory of "structural holes" where the advantages of serving as an intermediary or bridge between agents that are otherwise not directly connected is highlighted (see e.g., Kleinberg et al., 2008). On the contrary, it would not be efficient to link two already central nodes as their diffusion potential would partly overlap and they are likely to be relatively close in the initial network already.

From a more quantitative perspective, the new links yield a sizeable efficiency gain for both nodes in the pair (in the 1.25–1.5 range, i.e. 25% to 50% increase). The gain being higher for countries that were very weakly connected in the initial network (such as Bolivia or Nigeria). From a policy oriented perspective, our results highlight the fact that new transfer relationships benefit not only the pair of countries concerned, but also have positive effects for the network as a whole because the total diffusion time is reduced. Furthermore, they complement the conclusion of the previous experiment by highlighting that more bilateral projects, e.g. of the CDM type, should be launched between core developed countries and developing countries that lie away from major commercial routes.

6. Conclusion

There is a strong emphasis in the recent academic literature and policy debate on the pivotal role of technological diffusion in the mitigation of climate change. However, the understanding of how technologies are diffused globally is rather limited. This is partly due to a lack of comprehensive datasets directly documenting the spread of specific technologies at the global scale and over long periods of time. Another major difficulty is that the diffusion network is generally unknown. Since taking a network perspective is crucial, to tackle this challenge, in this paper we propose a systemic approach to infer the network by maximizing the likelihood of the observed diffusion patterns. As an empirical application, we use a consolidated database on successive generations of wind turbines adopted worldwide since the early 1980s.

Our main contributions are to first provide a better understanding of how wind energy technologies have diffused globally, then to quantitatively analyze structural properties of the network at the global, regional, and country-level, and finally to use the inferred network to characterize strategies with the aim of maximizing the spread of new technologies. Among the main results, it is found that (i) the degree distribution of the network has fat tails (i.e. there are countries which are much more connected than expected if sizes were drawn from a normal distribution), (ii) centrality is uniformly distributed among top countries reflecting the multipolar nature of the network, and (iii) the path length and diameter is relatively large, indicating there might be significant lags between advanced and developing countries in technology adoption. Against this background and geopolitical context of climate policy, we assess via simulations if transfer strategies tailored towards the diffusion of technologies to subgroups of developing countries can be more efficient than those based on conventional centrality measures. We show in particular that CDM projects that were mainly focused on large emerging economies did not pay sufficient attention, from the point of view of technology transfers, to the positive externalities that alternative targets among developing countries could have yielded.

There are promising avenues for further research. First, in view of providing a global assessment of the contribution of technology transfers to climate change mitigation, the proposed approach can be extended to a comprehensive portfolio of technologies, including other renewables such as solar power, innovations in energy-intensive manufacturing processes or transport. In this respect, preliminary results about the electric vehicle industry are provided in the Appendix. They highlight the possibility to extend our approach and show how the diffusion processes can be compared, as they are most likely to differ across the technologies and thus imply different climate policy strategies. This approach could also be germane in a wider context to study other types of global transfer mechanisms.

Now, the major question that the paper leaves unanswered is that of the determinants of the formation of technological diffusion networks. Bridging this gap in the literature on the econometrics of network formation could provide insights on the impacts of international trade and climate agreements on technological diffusion, and hence clarify how new forms of international cooperation such as climate clubs (Grubb et al., 2015; Nordhaus, 2015) could contribute to climate change mitigation through technological diffusion.

Appendix A. Supplementary Data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2017.11.023.

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